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ESTIMATING THE FUNCTIONAL FORM OF ROAD TRAFFIC MATURITY

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ABSTRACT

It has been observed that older high traffic motorways experience lower traffic growth than newer ones (*ceteris paribus*). This phenomenon is known as traffic maturity; however, it is not captured through traditional time-series long-term forecasts, due to constant elasticity to GDP these models assume. In this paper we argue that traffic maturity results from decreasing marginal utility of transport. The elasticity of individual mobility with respect to the revenue tends to decrease when the level of mobility increases. In order to find evidences of decreasing elasticity we analyse a cross-section time-series sample including 40 French motorways' sections. This analysis shows that decreasing elasticity can be observed in the long term. We then propose a decreasing function for the traffic elasticity with respect to the economic growth, which depends on the traffic level on the road. This model provides a good explanation for the observed traffic evolution and gives a rigorous econometric approach to time-series traffic forecasts.

KEY WORDS: traffic growth, traffic maturity, demand forecast, elasticity.

1. INTRODUCTION

The link, or coupling, between traffic and economic growth is a strong concept in transport and regional planning. In aggregated models of transport demand forecast, individual mobility and revenue are represented by traffic and gross domestic product (GDP). Mobility generates traffic and we suppose that growth in GDP leads to growth in purchase power. In economics, this link is represented by an elasticity of traffic with respect to the GDP, usually greater than one.

We can observe that older high traffic motorways experience lower traffic growth than newer, low traffic, ones (*ceteris paribus*). This phenomenon is known as traffic maturity in analogy with market maturity, a well known stage of products lifecycle. The maturity is not captured through traditional time-series long-term forecasts, due to constant elasticity to GDP these models assume. However, the observation of long traffic growth series put in evidence a growth deceleration in the long term.

In this sense we argue that the application of traditional traffic forecast models using time series with constant elasticity of traffic with respect to the GDP produces high growth hypothesis, leading to traffic overestimation when applied in forecasts. This paper aims at putting in evidence a decreasing relationship between the traffic level and the elasticity of the traffic with respect to economic growth and proposes a new econometric formulation for the time-series traffic forecast which considers the elasticity of traffic with respect to the GDP as a function of traffic level. Results show that this new model produces more reliable and precise forecasts.

The paper is organized as follows: section 2 presents the stages of traffic growth and the traditional econometric approach. Section 3 proposes that traffic maturity is a direct consequence of the decreasing marginal utility of transport. In section 4 we present the Partial Adjustment Model and the Error Correction Model. Section 5 puts in evidence the decreasing of elasticity over the traffic lever using data from 40 cross-sections time series sample. Section 6 proposes the new model and shows the impact in long-term forecasts. Section 7 briefly concludes the paper.

2. TRAFFIC GROWTH

In transport demand forecasts, whether for road, rail or air link, three growth stages are identified: the ramp-up, the traffic growth and the maturity. Ramp-up describes the delay traffic needs to reach its market share. The ramp-up period reflects the users' lack of familiarity with the new infrastructure and its benefits. The ramp-up period is characterized by a high traffic growth, from a level that is lower than expected as the equilibrium. An important phenomenon acting during the initial years is the induced traffic. Induced traffic is the increment of new vehicle traffic resulting from a road capacity improvement, which represents the latent demand.

When the short term impacts get over, the traffic evolution results from the growth in demand, which comes from the economic and population growths and the impact of monetary costs (toll, fuel and operating costs) on the route chosen and on alternative routes and modes.

Once a certain level is reached, traffic grows slower, giving evidence that the need for transport was satisfied. Disregarded in transport, market maturity is nevertheless a main issue in new products market analysis, for which the life cycle is shorter and concurrence stronger than in transport sector, in which this phenomenon has been recognized and studied at first in the air transport for tourism (Department for Transport, 1997; Graham, 2000); the possibilities to go on holidays been constrained, we should expect traffic will not grow unlimitedly.

The volume of traffic on a motorway can be assumed to depend on the level of economic activity, on the monetary and time costs of the motorway and on those of the alternative route and modes, as well as on the transport system characteristics. Monetary cost is defined as the sum of three components: toll, fuel price and other vehicle operating costs. Besides, given that demand for transport is a derived demand, other variables that have an effect on traffic should also be included in the equation. In this case, traffic volume in a specific motorway section is assumed to depend on the capacity of traffic emission and attraction of origins and destinations. The model can therefore be expressed as follows (Matas and Raymond, 2003):

$$(1)\quad \begin{aligned} T_{i,t} &= \alpha + \alpha_{1i} GDP_t + \alpha_{2i} FP_t + \alpha_{3i} Toll^M_{i,t} + \alpha_{4i} VC^M_{i,t} + \\ &\alpha_{5i} TC^M_{i,t} + \alpha_{6i} VC^C_{i,t} + \alpha_{7i} TC^C_{i,t} + \alpha_{8i} E_i + \alpha_{9i} A_i + \varepsilon_{i,t} \end{aligned}$$

where the subscriptions i refers to the motorway section and t to the period. $T_{i,t}$ is the traffic volume, GDP_t is the level of economic activity, FP_t = fuel price, $Toll^M_{i,t}$ is the motorway toll, $VC^j_{i,t}$ are other vehicle operating costs, j=M, C refer to motorway and alternative modes, respectively, $TC^j_{i,t}$ are the time costs, E_i is the emission factor and A_i is the attraction factor.

However, in the context where this estimation takes place it can be assumed that other vehicle operating costs and time costs remain constant over time. Thus, it is assumed that $VC^j_{i,t}$= VC^j_i and $TC^j_{i,t}$= TC^j_i. Therefore, after substitution, we get:

$$(2)\quad \begin{aligned} T_{i,t} &= \left[\alpha + \alpha_{4i} VC^M_{i,t} + \alpha_{5i} TC^M_{i,t} + \alpha_{6i} VC^C_{i,t} + \alpha_{7i} TC^C_{i,t} + \alpha_{8i} E_i + \alpha_{9i} A_i\right] \\ &+ \alpha_{1i} GDP_t + \alpha_{2i} FP_t + \alpha_{3i} Toll^M_{i,t} + \varepsilon_{i,t} \end{aligned}$$

Thus, the demand equation can be re-written as:

$$(3)\quad T_{i,t} = \alpha_{0i} + \alpha_{1i} GDP_t + \alpha_{2i} FP_t + \alpha_{3i} Toll^M_{i,t} + \varepsilon_{i,t}$$

where α_{0i} captures the terms in brackets in equation (2). This equation is usually applied on the log-log form. This transformation reduces heteroscedasticity and gives a convenient interpretation of results, which can be read directly as elasticities. The equation becomes:

$$(4)\quad \log(T_{i,t}) = \alpha_{0i} + \alpha_{1i} \log(GDP_t) + \alpha_{2i} \log(FP_t) + \alpha_{3i} \log(Toll^M_{i,t}) + \varepsilon_{i,t}$$

This model, henceforth called LTM, for long-term model, represents a long-term equilibrium between the variables. The elasticity of traffic with respect to the *GDP* in section *i* is α_1 because:

$$(5)\ \varepsilon_{T/PIB} = \frac{GDP}{T}\frac{\partial T}{\partial GDP} = \frac{\partial \log(T)}{\partial \log(GDP)} = \alpha_1$$

This constant elasticity specification is generally used in empirical studies but it is however questionable since we could expect the elasticity to be decreasing; this argument is developed in the next session.

3. WHY DOES TRAFFIC GROW DECREASINGLY?

The consumer theory, from its classic axioms, transforms preferences in utility. The law of decreasing marginal utility states that marginal utility decreases as the quantity consumed increases. In essence, each additional good consumed is less satisfying than the previous one. This law holds for most goods, and do so for transport. This principle supports the idea of decreasing transport growth since the utility of an additional travel depends on individual's mobility. Furthermore, time and money constraints limit transport possibilities.

New traffic comes from new users on the route or mode and from existent users making more or longer trips. The traffic increment due to new users results from population growth as well as changes in land use and in locations of economic activities. Furthermore, reductions in transport costs as well as increases in user's wealth allow people to travel more and more often. This is particularly evident in the case of the air transport sector, where price reductions due to competition in the last years had not only diverted users from other modes but also allowed less rich people to afford air travels.

For existing users, the reduction on generalized costs, increasing in wealth and reduction and flexibility of working time allow users to travel more often. The possibility of supplementary trips is however constrained by time (daily time and holidays) and money availability. Budget and time depend not only on transport itself but on time and money spent in all others activities. These constraints unequally affect different people and different population classes. A retired person is supposed to be more constrained by money than by time, inversely to a rich businessman.

In addition to budget and time constraints, there is the desire to travel. We can reasonably suppose that the higher is the individual's mobility level, the lesser will be his inclination or necessity to make one more trip. Despite regular fluctuations in transport demand, i.e. seasonal peaks, it has been suggested (for example, by Thomson, 1974) that over time, there has been a remarkable stability in the demand for travel, with households, for example, on average making roughly the same number of trips during a day albeit for different purposes or by different modes. There may be more leisure travel, but there are fewer work trips and greater is now made of air transport and the motor-car at the expense of walking and cycle. It is suggested that this situation reflects the obvious fact that there is a limit to the available time people have for travel, especially if they are to enjoy the fruits of the activities at the final destinations (Button, 1993).

This phenomenon is formulated as the decreasing marginal utility of travel, which means that $U(t)>0$, $U'(t)>0$ and $U''(t)<0$, where $U(t)$ is the utility associated with transport. The utility function and constraints compose the individual's utility maximization program, where individual make trade-offs between possible allocations of resources. Utility functions define choices which generate demand functions, from which elasticities can be derived. Elasticities give adimensional measures of sensibility of a variable with respect to another. Elasticities are then concise measures of preferences and reflect the sensibility to changes in a limited resources environment (figure 1).

(figure 1 about here)

The ordinary or Marshallian demand function is derived from consumers who are postulated to maximize utility subject to a budget constraint. As a good's price changes, the consumer's real income (which can be used to consume all goods in the choice set) changes. In addition the goods price relative to other goods changes. The changes in consumption brought about by these effects following a price change are called *income* and *substitution* effects respectively. Thus, elasticity values derived from the ordinary demand function include both income and substitution effects (Gillen and al, 2004).

In this sense, the elasticity of individual mobility with respect to the revenue decreases with the level of mobility. In aggregated terms, the superposition of individuals behaviours results in an increment in traffic which is decreasing in the part of traffic generated by existing users and therefore for economic and population constant growth, globally decreasing.

Congestion also constrains traffic growth. It has a double effect, first it physically limits traffic growth and second it reduces the generation of traffic by increasing the generalised cost. Nevertheless, traffic maturity must be isolated of congestion. Traffic maturity is a pure demand effect while congestion comes from the interaction of a level of demand higher then infrastructure capacity. We argue that maturity do not depends on supply (while traffic does). This argument is valid if we consider that congestion is limited to special periods (holidays departure) or a particular OD pair, affecting at the individual level, while our analysis focuses in a more aggregated level.

4. ECONOMETRIC ISSUES

Partial Adjustment

The model (4) implies a long-run relationship between the variables; in any given period, actual demand could only be expected to be in equilibrium with (and so to be completely explained by) the income and costs associated in each period. However, the persistence of habit, uncertainty and incomplete information are some reasons why complete adjustment could not be achieved in a single period. In this case, the desired demand in year *t*, $T*_{i,t}$ is not equivalent to the actual demand in *t*, $T_{i,t}$. Although behavioural adjustment is towards the equilibrium, only a proportion, θ, of the gap between the desired (equilibrium) demand and actual demand is closed each year. This can be written as:

$$(6)\, T_{i,t} - T_{i,t-1} = \theta(T*_{i,t} - T_{i,t-1})$$

where θ ($0 \le \theta \le 1$) is the adjustment coefficient, which indicates the rate of adjustment to long-term equilibrium and reflects the inertia of economic behaviour. Rearranging (6) and substituting in (4) We obtain the following Partial Adjustment Model:

$$(7)\log(T_{i,t}) = \theta\alpha_{0i} + \theta\alpha_{1i}\log(GDP_t) + \theta\alpha_{2i}\log(FP_t) + \theta\alpha_{3i}\log(Toll^M_{i,t}) + (1-\theta)\log(T_{i,t-1}) + \varepsilon_{i,t}$$

or equivalently:

$$(8)\log(T_{i,t}) = \alpha_{0i} + \alpha_{1i}\log(GDP_t) + \alpha_{2i}\log(FP_t) + \alpha_{3i}\log(Toll^M_{i,t}) + \phi\log(T_{i,t-1}) + \varepsilon_{i,t}$$

where the short-run elasticities are given by the coefficients α 's and the long-run elasticities are the ratio of the short-run value by 1-ϕ.

Integrated variables, Cointegration and Error-Correction

Most time-series techniques need data to be stationary, but this requirement is often not fulfilled by economic series, which tend to increase over time. Those problems were somehow ignored in applied work until important papers by Granger and Newbold (1974) and Nelson and Plosser (1982) alerted many to the econometric implications of non-stationarity and the dangers of running *nonsense* or *spurious* regressions.

A non-stationary series can be made stationary by detrending series. A convenient way of detrending is by using first differences rather than levels of the variables. A non-stationary series which can be made stationary by differencing *d* times is said to be integrated of order *d*, denoted $x_t \sim I(d)$, a stationary series is a *I(0)* series (Engle and Granger, 1987).

While removing trending by differencing can actually be a statistical satisfactory solution, it represents a lost of economic information about the long-term relationship. However, for some time it remained to be well understood how both variables in differences and levels could coexist in regression models. Granger (1981), resting upon the previous ideas, solved the puzzle by pointing out that a vector of variables, all of which achieve stationarity after differencing, could have linear combinations which are stationary in levels. Later, Engle and Granger (1987) were the first to formalize the idea of integrated variables sharing an equilibrium relation which turned out to be either stationary or have a lower degree of integration than the original series. They denoted this property by *cointegration*, signifying co-movements among trending variables which could be exploited to test for the existence of equilibrium relationships within a fully dynamic specification framework. In this sense, the basic concept of cointegration applies in a variety of economic models. A humorous illustration of this concept is given by Murray (1994) and extended by Smith and Harrison (1995).

Before proceeding with the cointegration analysis, it is necessary to verify whether the variables under consideration are stationary, and if not, check their orders of integration. This can be accomplished using the *unit-root* test. The most widely used unit-root test is the Augmented Dicky-Fuller (ADF) test (Greene, 1997). This test was applied for each section as well as for the independent variables in logarithms. The null hypothesis of unit root was always non-rejected. Various methods have been suggested to test for cointegration. One method is to estimate the long-run relationship by OLS and testing whether the residual is stationary. The hypothesis of unit roots of residuals could not always be rejected. However, it should be stressed that unit-root tests in general do not produce unambiguous results. They are large sample tests and their behaviour in small samples is questionable. Given these problems, any results regarding the stationarity or non-stationarity of a particular series must be treated with caution (Dargay and all, 2002).

According to the Granger Representation Theorem, cointegrated series can be represented by an Error Correction Model. The dependent variable in an Error-Correction Model (ECM) is specified in terms of differences, rather than levels. ECM are well suited in cointegrated relationships since they incorporate the long-run relationships as well as the dynamics implied by the deviations from this equilibrium path and the adjustment process to recover it. The ECM can be written as (Dargay and all, 2002):

$$(9)\; \Delta T_t = \alpha_0 + (\varphi - 1)T_{t-1} + \beta_0 \Delta X_t + (\beta_0 + \beta_1) X_{t-1} + \varepsilon_{it}$$

where X is the vector of explanatory variables. More general forms could include higher order lagged differenced terms of the independent variables and lagged differences of the dependent variables. The model (9) can alternatively be written as:

$$(10)\; \Delta T_t = \alpha_0 + \beta_0 \Delta X_t + (\varphi - 1)\left[T_{t-1} + \frac{(\beta_0 + \beta_1)}{(\varphi - 1)} X_{t-1} \right] + \varepsilon_{it}$$

The parameter β_0 represents the short-term effect and $(1\text{-}\varphi)$ is the feedback effect, which is similar to the adjustment coefficient, θ, in the Partial Adjustment Model. The long-run response is given by $(\beta_0 + \beta_1)/(1 - \varphi)$. The term in the square brackets in equation (A5) is called an "error-correction mechanism" since it reflects the deviation from the long run, with $(1 - \varphi)$ of this deviation being closed each period. The Error Correction Model allows estimation of both short- and long-run parameters simultaneously. If the error-correction term $(\varphi - 1)$ is significantly different from zero and negative (since $0 < \varphi < 1$) the variables are cointegrated and the estimated parameters of the lagged level variables define the long-run relationship. The estimated model then takes the following form:

$$(11)\; \begin{aligned} &\Delta \log(T_{i,t}) = \beta_{0i} + \beta_{1i} \Delta \log(GDP_t) + \beta_{2i} \Delta \log(FP_t) + \beta_{3i} \Delta \log(Toll^M_{i,t}) + \\ &\alpha_{1i} \log(T_{i,t-1}) + \alpha_{2i} \log(GDP_{t-1}) + \alpha_{3i} \log(FP_{t-1}) + \alpha_{4i} \log(Toll^M_{i,t-1}) + \varepsilon_{i,t} \end{aligned}$$

Data and Estimation

The data used in this analysis comes from the ASFA (Federation of French motorways concessionaries). Our sample includes 40 French motorway's sections with traffic series longer than 15 years, in different French regions and including all the main concessionaires (ASF, APRR, COFIROUTE, SANEF and SAPN). The GDP series comes from the INSEE (National Institute for Statistics and Economic Studies). The series of toll prices for all concessionaires were provided by the the Department of Traffic and Economic Studies of COFIROUTE.

For each section and each model (LTM, PAM and ECM), we begin with a general specification which includes all explanatory variables, and proceed to exclude those which are either implausible because of magnitude or sign or insignificant in a statistical sense.

5. EVIDENCES OF DECREASING GROWTH

A concavity can be observed for the last periods in many long-term traffic series. Figure 2 shows this decreasing of growth in two French motorways. The issue here is to understand whether this deceleration of the growth indicates that the maturity had been reached or it results from an economic deceleration, an increasing in fuel costs or other factors.

(figure 2 about here)

In order to find evidences that this decreasing growth results from a decreasing elasticity we proceed to a three steps analysis. First, we estimate the long-run elasticity of traffic with respect to the GDP using the three models presented earlier. Second, we test for the statistical stability of parameters on these sections using the CUSUM[2] tests. Finally, we segment the sample in order to observe the evolution of elasticities.

Cross-section time series analysis

We applied the LTM, PAM and ECM for the 40 sections in order to determine the (constant) elasticity of traffic with respect to the GDP (results are presented in appendix 1).

Plotting the long-run elasticity of the traffic with respect to the GDP over the traffic level in the first period (max(1980, opening date)) we can observe a clear decreasing relationship, i.e. sections with a high traffic at opening present a lower elasticity.

(figure 3 about here)

This result is however much less evident for the short-run elasticities. Some decreasing relationship can be found using the ECM but not with the PAM, moreover, many short-run elasticities are not statistically significant. This result can be viewed in figure (4).

(figure 4 about here)

An interesting issue here is to see whether the three models produce comparable elasticities. Comparing the statistical significant (at 90% level) long-run elasticities estimated by the LTM, PAM and ECM (appendix 1) we can see that results are quite similar in the three models for most sections and, it seems that, in average, the PAM tends to produce slightly higher elasticities than the other models. Despite its incapacity of estimating short-run elasticities the LTM has the strong advantage of allowing for more robust estimates. It is the only model which produces statistical significant elasticities for every section.

Testing for parameter stability

Proposed by Brown, Durbin and Evans (1975) the $CUSUM^2$ (or CUSUM of squares) test for the constancy over time of the coefficients of a linear regression model. This tests is based on recursive residuals (the $CUSUM^2$ is preferred to the CUSUM due to its higher power). This test was applied in the fits provided by (4). Results are shown in appendix 1 where 0 represents the validity of the null hypothesis (constancy of parameter) and 1 indicates that coefficients do not remain constant during the full sample period at 95% of significance. The null hypothesis of stability was rejected in 29 cases.

Moving regressions

The relationship between long-run elasticities and the traffic level shows that high traffic level motorways tend to have smaller elasticities and the cusum of squares test show that parameters may be varying over time. The link between these two results will be to show that within each section, the elasticity is decreasing. A simple diagnostic test to detect the decrasing of the parameter is to partition the sample into subsamples of approximated equal number of observations each. We set 2 subsamples of approximately 15 years (with overlapping). Results in appendix 1 (ss_1 and ss_2 for subsamples 1 and 2 respectively) show that a globally decreasing elasticity can be observed in all but 2 sections, and in most cases, the elasticity in the second period is also smaller than the lower bound (95%) of the first subsample.

6. A FUNCTIONAL FORM FOR DECREASING ELASTICITY

There are different ways to specify declining elasticities. Some studies (as in Dargay et all, 2002) propose "inconditional" declining elasticites by replacing the log of GDP by the inverse of some function of GDP (GDP, log(GDP), or other). Dargay et all (2002) find that declining elasticities are more arguable and provide statistically better adjustments.

Precedent results and the theoretical arguments explained before lead us to consider a variable relation between traffic and economic growths by an elasticity depending on the traffic level. To take in account the asymptotically decreasing put in evidence, we propose the following formulation:

$$(12)\ \varepsilon_{T/GDP}(T) = \frac{\partial T / T}{\partial GDP / GDP} = k.T^{\gamma}$$

where k is a positive constant and γ is a negative constant. Although an exponential or logistic form could be suitable, this functional form was preferred due to its convenient form, leading to readable parameters. The parameter γ may be interpreted as the elasticity of the -elasticity of traffic with respect to the GDP- with respect to the traffic level, since:

$$(13)\, \varepsilon_{\varepsilon_{T/GDP}/T} = \frac{\partial \varepsilon_{T/GDP}}{\partial T} \frac{T}{\varepsilon_{T/GDP}} = \gamma.k.T^{\gamma-1}.\frac{T}{kT^{\gamma}} = \gamma$$

The differential equation (14) is separable and its solution (for $\gamma \neq 0$) is:

$$(14)\, T = (-\gamma.(k.\log(GDP) + c))^{-\frac{1}{\gamma}}$$

Where c is the constant from the integration. Assuming that this relation holds for the first period (T_1, GDP_1) and both T_1 and GDP_1 are normalized to one then T becomes:

$$(15)\, T = (1 - \gamma.k.\log(GDP))^{-\frac{1}{\gamma}}$$

The equation (4) can be therefore rewritten as:

$$(16)\ \log(T_{i,t}) = \alpha_{0i} - \frac{1}{\gamma_i}\log\left(1 - \gamma_i.k_i.\log(GDP_t)\right) + \alpha_{2i}\log(FP_t) + \alpha_{3i}\log(Toll_{i,t}^{M}) + \varepsilon_{i,t}$$

This approach sets up an intrinsic relation between the traffic level and its reactivity to economic growth; it provides a good representation of the phenomenon and a convenient interpretation of results at the cost of introducing a non-linearity in the demand equation.

Estimated γ and k are reported in appendix 1. Results provide very good fits and proper values, except in two cases, for which we estimated positives values for γ (for the same sections where the moving regressions indicated a growth instead of a decreasing of the elasticities), indicating that the maturity has not been reached; these values shall be used with care for forecast purposes. Figure 5 compares the constant and the variable elasticity for section 40; the vertical line represents the ratio between the traffic in the last and in the first periods.

(figure 5 about here)

The same principle can be applied to the PAM and to the ECM. For these models we can apply two different approaches. The first one consists in setting a decreasing parameter for the GDP, as for the LTM. This will nevertheless imply a decreasing short-run elasticity for the PAM. The second approach is, instead of setting a decreasing coefficient with respect to the GDP, consider a growth of the adjustment coefficient (θ in the PAM and φ-1 in the ECM) following the same pattern. This formulation leads to the same results in terms of long-run elasticities and is consistent with the economic intuition behind the hypothesis of decreasing elasticity.

Writing $\phi = k.T^{\gamma}$ in the PAM, equation (8) becomes:

(17)

$$\log(T_{i,t}) = \alpha_{0i} + \alpha_{1i}\log(GDP_t) + \alpha_{2i}\log(FP_t) + \alpha_{3i}\log(Toll_{i,t}^{M}) - \frac{1}{\gamma_i}\log\left(1 - \gamma_i.K_i.\log(T_{i,t-1})\right) + \varepsilon_{i,t}$$

and the long-run elasticities will be given by the ration of the short-run value by $1\text{-}k_i.T_{i,t}^{\gamma_i}$, where $0<k_i<1$ and $\gamma_i<0$.

Making $(\varphi - 1) = k.T^{\gamma}$ (where k will be negative and γ positive) the ECM (11) can be re-written as

$$\begin{aligned}&\Delta\log(T_{i,t}) = \beta_{0i} + \beta_{1i}\Delta\log(GDP_t) + \beta_{2i}\Delta\log(FP_t) + \beta_{3i}\Delta\log(Toll_{i,t}^{M})\\ &-\frac{1}{\gamma_i}\log\left(1 - \gamma_i.K_i.\log(T_{i,t-1})\right) + \alpha_{2i}\log(GDP_{t-1}) + \alpha_{3i}\log(FP_{t-1}) + \alpha_{4i}\log(Toll_{i,t-1}^{M}) + \varepsilon_{i,t}\end{aligned} \quad (18)$$

The long-run elasticities will be given by $\alpha_{2i} / -k_i T_{i,t}^{\gamma_i}$.

Impact on long-term forecasts

As we can see in figure 5, if the elasticity decreases with the traffic growth, the assumption of a constant elasticity will tend to overestimate the future traffic.

Consider the hypothetical case in figure 6a where both initial traffic is GDP are normalized to 1, the constant elasticity is 2.0, k=2.5 and γ=-0.5. We can see that in the short term results from both models are very close. As the GDP increases the difference becomes more important; the classic model presents a globally convex profile while the new model produces a concave evolution.

This approach was applied in a large scale forecast traffic until 2030 to the main French private motorways. One example is given in the figure 6b; both models presented very good fits (R^2>0.98). Results show that the variable elasticity model produces more conservative forecasts. Moreover, estimating both models using data until 1999 and comparing the forecasts between 2000 and 2005 with the actual traffic we can see that the variable elasticity model was twice more precise.

(figure 6 about here)

This method is however very data greedy. If no information on parameters is inferred, a quite long data series is needed to calibrate the model but it confers a significant advantage in terms of results for very long-term forecasts for which the constant elasticity seems to be an unrealistic and overoptimistic hypothesis.

7. CONCLUSIONS

In this paper we put in evidence the decreasing of the elasticity of traffic with respect to the GDP, which characterises the traffic maturity and have shown that the hypothesis of constant elasticity assumed by classic models is unrealistic and leads to overoptimistic traffic projections.

A new model of decreasing elasticity is proposed setting up an intrinsic relation between the traffic level and its reactivity to economic growth. This model allows for a good representation of the phenomenon, a good interpretation of results and gives a rigorous econometric approach to time-series traffic forecasts, at the cost of introducing a non-linearity in the equation. In the short term the model results are closer to that given by the classical constant elasticity model; in the long term, where classic models tend to produce linear or convex profiles, this model reproduces the observed concavity. This model allows for a better interpretation of the coupling between traffic and economic growth, and a better long-term forecast.

Although our analysis focus on toll motorways, we believe that the principle exposed and validated here is valid for any interurban road; the magnitude of impacts should however be different. This hypothesis remains to be validated.

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Appendix 1: Summary of results.

ID	L	$year_0$	$traffic_0$	elt (LTM)	esr (PAM)	elr (PAM)	esr (ECM)	elr (ECM)	$cusum^2$	elr (ss_1)	elr (ss_2)	γ	k
1	25	1980	21090	1.15	0.65	1.24	0.71	1.38	1	1.39	0.42	-1.55	2.04
2	18	1987	2362	6.03	0.82	2.69	(1.03)	(2.86)	1	9.36	2.09	-0.13	10.70
3	25	1980	24164	1.84	0.42	2.50	(-0.07)	(0.42)	1	2.26	0.59	-1.24	4.24
4	25	1980	6177	4.17	1.95	5.84	(1.41)	4.60	0	4.29	1.77	-0.12	4.26
5	25	1980	5499	1.95	0.54	2.44	(0.16)	(1.37)	1	2.43	1.42	-0.93	4.10
6	22	1983	4630	5.02	1.76	5.34	1.69	(3.39)	1	5.08	3.62	-0.51	8.99
7	22	1983	662	6.71	(1.26)	(9.56)	(0.66)	(7.86)	1	9.26	3.98	-0.12	7.62
8	20	1985	1532	9.35	(0.39)	(1.27)	(1.02)	6.48	0	11.31	2.19	-0.24	19.65
9	25	1980	13456	2.37	0.62	2.32	0.58	(1.47)	1	2.44	1.51	-0.70	4.03
10	25	1980	7541	2.43	0.45	2.01	1.29	1.94	0	2.26	2.54	0.50	1.80
11	25	1980	6002	3.54	0.83	3.88	(0.19)	2.23	0	4.08	1.68	-0.35	5.28
12	25	1980	6296	3.23	1.37	3.48	0.95	3.20	1	3.94	2.16	-0.44	4.98
13	25	1980	4505	4.11	1.90	5.17	(0.95)	4.40	0	5.07	1.87	-0.28	5.67
14	25	1980	24111	2.00	1.15	2.18	(0.68)	2.15	1	2.21	1.65	-0.45	2.56
15	25	1980	4332	3.76	1.09	4.47	1.18	3.78	1	4.44	2.44	-0.42	6.12
16	25	1980	16252	2.35	0.96	2.52	(0.56)	2.34	0	2.58	2.01	-0.46	3.17
17	25	1980	8709	2.04	(0.38)	(1.95)	(0.63)	1.89	0	2.18	2.15	-0.40	2.62
18	25	1980	2917	4.43	(0.26)	(2.09)	1.44	2.32	1	5.33	2.22	-0.43	8.73
19	25	1980	2768	4.51	1.13	3.69	(0.81)	3.33	0	4.81	2.73	-0.10	5.26
20	25	1980	6565	2.94	0.86	2.93	(0.75)	2.37	1	3.29	2.26	-0.44	4.47
21	24	1981	8370	3.11	1.21	3.23	1.05	2.60	1	3.36	1.98	-0.37	4.21
22	18	1987	6494	2.97	0.86	2.22	(-0.90)	2.22	0	2.05	2.26	0.77	1.38
23	25	1980	28854	2.34	0.80	2.67	1.01	(2.55)	1	2.89	1.03	-0.68	3.90
24	25	1980	11130	2.19	0.79	2.81	0.63	(2.47)	1	3.05	0.91	-0.80	4.74
25	25	1980	4146	3.70	1.07	3.85	2.21	(4.27)	0	3.46	2.02	-0.21	5.02
26	25	1980	10236	2.33	0.73	3.02	0.98	2.95	1	3.13	0.88	-0.82	4.75
27	25	1980	4159	4.92	1.75	5.03	3.04	4.11	1	5.34	1.53	-0.21	7.23
28	25	1980	5507	2.40	0.26	2.62	(0.32)	2.25	1	3.41	0.87	-1.20	5.58
29	25	1980	17540	2.42	1.59	2.47	1.39	2.42	1	2.60	2.35	-0.68	2.99
30	25	1980	14332	2.28	1.16	2.51	0.75	2.41	1	2.52	2.17	-0.67	3.30
31	19	1986	5835	2.14	0.32	1.37	(-0.54)	1.41	1	2.64	1.40	-0.80	4.01
32	25	1980	22402	2.19	0.72	2.63	(0.55)	2.00	1	2.49	1.26	-0.80	4.01
33	25	1980	7162	2.73	0.88	3.33	(0.42)	3.07	0	2.98	1.34	-0.37	3.80
34	25	1980	3074	3.18	(0.46)	(3.88)	(-0.19)	(2.35)	1	3.64	1.55	-0.53	5.46
35	23	1982	1138	6.94	1.45	5.89	(1.31)	6.83	1	7.17	2.11	-0.42	16.05
36	25	1980	8130	2.67	(0.34)	(3.21)	0.73	(-0.18)	1	3.36	1.24	-0.77	6.57
37	25	1980	4496	3.37	0.62	4.49	(0.59)	(0.44)	1	4.12	1.55	-0.52	7.16
38	25	1980	7777	2.73	0.90	3.70	(1.00)	3.38	1	3.16	1.52	-0.41	4.52
39	25	1980	5700	2.71	0.74	4.15	1.07	4.15	1	3.15	1.33	-0.56	4.94
40	25	1980	11834	3.04	1.17	3.33	0.87	3.04	1	2.84	1.55	-0.44	3.85

L is the series lenght ; $traffic_0$ is the traffic in the minimum of the opening date and 1980; elr and esr are the long and short-run elasticities, respectively;

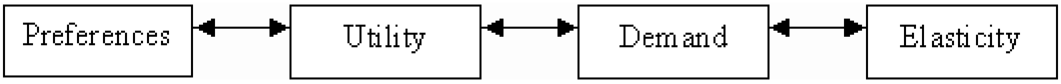
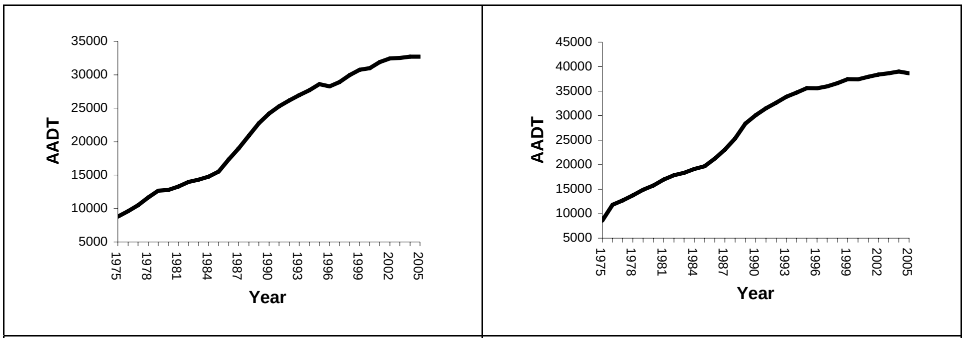
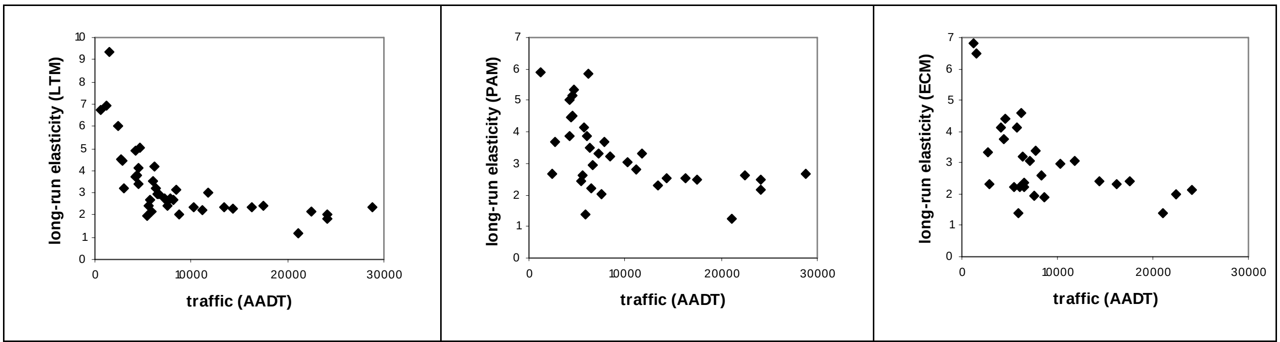


Figure 1: From preferences to elasticity



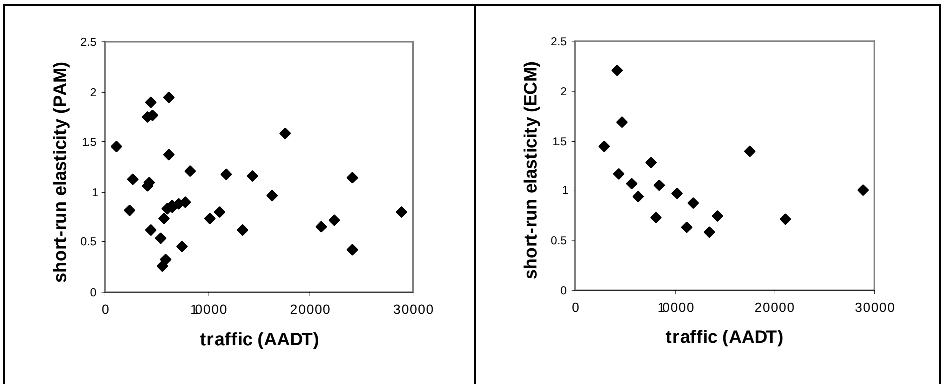
(a) Traffic on the A10 motorway	(b) Traffic on the A11 motorway

Figure 2: Traffic growth



(a) long-run elasticity LTM	(b) long-run elasticity PAM	(c) long-run elasticity ECM

Figure 3: Decreasing elasticities



(a) short-run elasticities PAM	(a) short-run elasticities ECM

Figure 4: Short-run elasticities

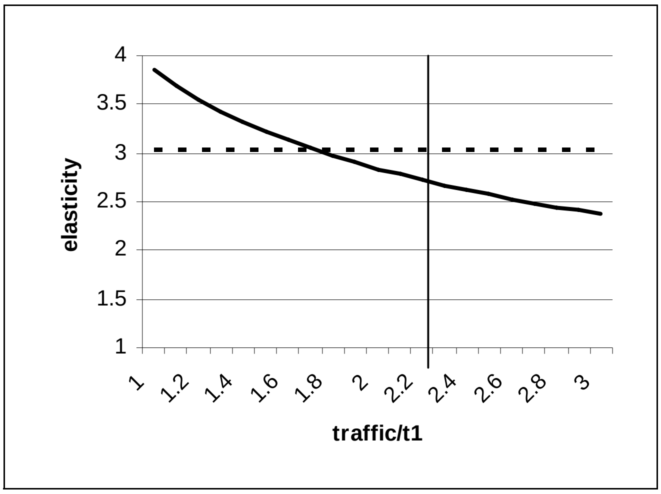
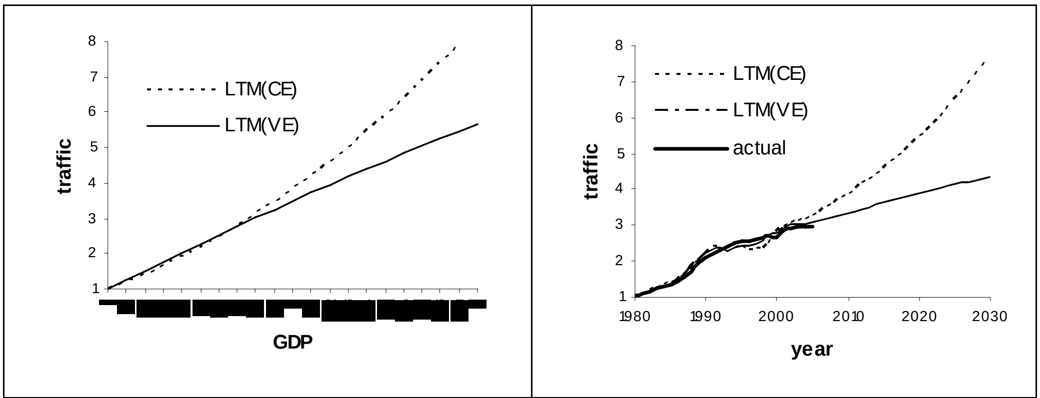


Figure 5: Comparing elasticities



(a) hypothetical example | (b) application to the A11 motorway

LTM(CE) is the forecast using constant elasticity;
LTM(VE) is the forecast using variable elasticity;

Figure 6: Application of the new model.